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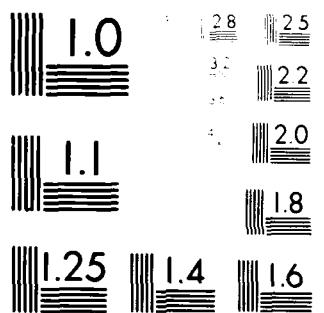
YALE UNIV NEW HAVEN CT DEPT OF COMPUTER SCIENCE
EFFICIENT IMPLEMENTATION OF A CLASS OF PRECONDITIONED CONJUGATE--ETC(U)

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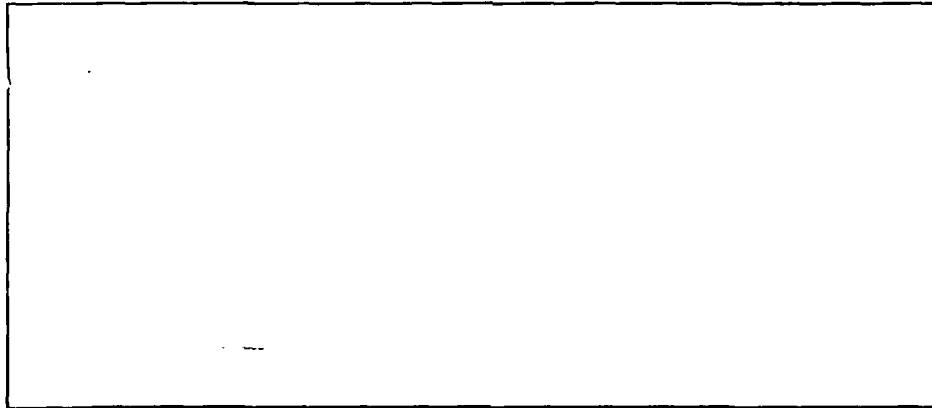
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Abstract

The preconditioned conjugate gradient (PCG) method is an effective means for solving systems of linear equations where the coefficient matrix is symmetric and positive definite.

The incomplete LDL^t factorizations are a widely used class of preconditionings, including the SSOR, Dupont-Kendall-Rachford, Generalized SSOR, ICCG(0), and MICCG(0) preconditionings. The efficient implementation of PCG with a preconditioning from this class is discussed.

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Efficient Implementation of a Class
of Preconditioned Conjugate Gradient Methods

(1) Stanley C. Eisenstat

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1. Introduction

Consider the system of N linear equations

$$(1) \quad A x = b,$$

where the coefficient matrix A is symmetric and positive definite. When A is large and sparse, the preconditioned conjugate gradient (PCG) method is an effective means for solving (1) [2, 4, 5, 9, 13]. Given an initial guess x_0 , we generate a sequence $\{x_k\}$ of approximations to the solution x as follows:

$$(2a) \quad p_0 = r_0 = b - Ax_0$$

$$(2b) \quad \text{Solve } Mr_0' = r_0$$

FOR $k = 0$ STEP 1 UNTIL Convergence DO

$$(2c) \quad \alpha_k = (r_k, r_k') / (p_k, Ap_k)$$

$$(2d) \quad x_{k+1} = x_k + \alpha_k p_k$$

$$(2e) \quad r_{k+1} = r_k - \alpha_k Ap_k$$

$$(2f) \quad \text{Solve } Mr_{k+1}' = r_{k+1}$$

$$(2g) \quad \beta_k = (r_{k+1}, r_{k+1}') / (r_k, r_k')$$

$$(2h) \quad p_{k+1} = r_{k+1}' + \beta_k p_k$$

The effect of the preconditioning matrix M is to increase the rate of convergence of the basic conjugate gradient method of Hestenes and Stiefel [11]. The number of multiply-adds per iteration is just $5N$, plus the number required to form Ap_k , plus the number required to solve $Mr_k' = r_k$.

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One widely used class of preconditionings are the incomplete LDL^t factorizations

$$(3) \quad M = (\tilde{D}+L) \tilde{D}^{-1} (\tilde{D}+L)^t,$$

where $A = L+D+L^t$, L is strictly lower triangular, and D and \tilde{D} are positive diagonal. This class includes the SSOR [9], Dupont-Kendall-Rachford [7], Generalized SSOR [1], ICCG(0) [13], and MICCG(0) [10] preconditionings.

Letting $NZ(A)$ denote the number of nonzero entries in the matrix A , a straight-forward implementation of PCG with a preconditioning from this class¹ would require $6N+2NZ(A)$ multiply-adds per iteration.²

In this brief note, we show how to reduce the work to $8N+NZ(A)$ multiply-adds, asymptotically half as many as the straight-forward implementation.³ We give details in Section 2, and consider some generalizations in Section 3.

2. Implementation

The linear system (1) can be restated in the form

¹ Writing M as $(\tilde{D}+L)(I+\tilde{D}^{-1}L^t)$, we solve $Mx'_k = r_k$ by solving the triangular systems $(\tilde{D}+L)t_k = r_k$, $(I+\tilde{D}^{-1}L^t)r'_k = t_k$.

² $2N$ (respectively, N) multiply-adds can be saved by symmetrically scaling the problem to make $\tilde{D} = I$ (respectively, $D = I$).

³ A similar speedup for pairs of linear iterative methods is given in [6].

$$(4) \quad [(\tilde{D}+L)^{-1} A (\tilde{D}+L)^{-t}] [(\tilde{D}+L)^t x] = [(\tilde{D}+L)^{-1} b]$$

or

$$(5) \quad \hat{A} \hat{x} = \hat{b}.$$

But applying PCG to (1) with $M = (\tilde{D}+L)\tilde{D}^{-1}(\tilde{D}+L)^t$ is equivalent to applying PCG to (5) with $\hat{M} = \tilde{D}^{-1}$ and setting $x = (\tilde{D}+L)^{-t}\hat{x}$.⁴ If we update x instead of \hat{x} at each iteration, algorithm (2) becomes:

$$(6a) \quad \hat{p}_0 = \hat{r}_0 = \hat{b} - \hat{A}\hat{x}_0$$

$$(6b) \quad \text{Compute } \hat{r}'_0 = \tilde{D}\hat{r}_0$$

FOR k = 0 STEP 1 UNTIL Convergence DO

$$(6c) \quad \hat{a}_k = (\hat{r}_k, \hat{r}'_k) / (\hat{p}_k, \hat{A}\hat{p}_k)$$

$$(6d) \quad x_{k+1} = x_k + \hat{a}_k (\tilde{D}+L)^{-t}\hat{p}_k$$

$$(6e) \quad \hat{r}_{k+1} = \hat{r}_k - \hat{a}_k \hat{A}\hat{p}_k$$

$$(6g) \quad \text{Compute } \hat{r}'_{k+1} = \tilde{D}\hat{r}_{k+1}$$

⁴ Both are equivalent to applying the basic conjugate gradient method to the preconditioned system

$$\bar{A}\bar{x} = [\tilde{D}^{1/2}(\tilde{D}+L)^{-1} A (\tilde{D}+L)^{-t}\tilde{D}^{1/2}] [\tilde{D}^{-1/2}(\tilde{D}+L)^t x] = [\tilde{D}^{1/2}(\tilde{D}+L)^{-1} b] = \bar{b}$$

(see [4], pp. 58-59).

$$(6g) \quad \hat{b}_k = (\hat{r}_{k+1}, \hat{r}'_{k+1}) / (\hat{r}_k, \hat{r}'_k)$$

$$(6h) \quad \hat{p}_{k+1} = \hat{r}'_{k+1} + \hat{b}_k \hat{p}_k$$

$\hat{A}\hat{p}_k$ can be computed efficiently by taking advantage of the following identity:

$$(7) \quad \begin{aligned} \hat{A}\hat{p}_k &= (\tilde{D}+L)^{-1} [(\tilde{D}+L) + (\tilde{D}+L)^t - (2\tilde{D}-D)] (\tilde{D}+L)^{-t} \hat{p}_k \\ &= (\tilde{D}+L)^{-t} \hat{p}_k + (\tilde{D}+L)^{-1} [\hat{p}_k - K(\tilde{D}+L)^{-t} \hat{p}_k], \end{aligned}$$

where $K = 2\tilde{D}-D$. Thus

$$(8a) \quad \hat{t}_k = (\tilde{D}+L)^{-t} \hat{p}_k$$

$$(8b) \quad \hat{A}\hat{p}_k = \hat{t}_k + (\tilde{D}+L)^{-1} (\hat{p}_k - K\hat{t}_k),$$

which requires $2N+NZ(A)$ multiply-adds. \hat{t}_k can also be used to update x_k in (6d), so that the total cost for each PCG iteration is just $8N+NZ(A)$ multiply-adds,⁵ versus $6N+2NZ(A)$ for the straight-forward implementation.

3. Generalizations

The approach presented in Section 2 extends immediately to preconditionings of the form

⁵ Again, $3N$ multiply-adds can be saved by symmetrically scaling the problem so that $\tilde{D} = I$.

$$(9) \quad M = (\tilde{D}+L) \tilde{S}^{-1} (\tilde{D}+L)^t ,$$

where \tilde{S} is positive diagonal. Moreover, if we take $K = \tilde{D} + \tilde{D}^t - D$ in (7) and (8), then \tilde{D} need not be diagonal or even symmetric. In this case, \tilde{D} would reflect changes to both the diagonal and off-diagonal entries of A in generating an incomplete factorization. If we assume that only the nonzero entries of A are changed, i.e., that $(K)_{ij}$ is nonzero only if $(A)_{ij}$ is nonzero, then the operation count is $7N + NZ(A) + NZ(K)$.

Another application is to preconditioning nonsymmetric systems. Let

$$(10) \quad M = (\tilde{D}+L) \tilde{S}^{-1} (\tilde{D}+U) ,$$

be an incomplete LDU factorization of a nonsymmetric matrix A , where $A = L+D+U$, L (respectively, U) is strictly lower (respectively, upper) triangular, and D and \tilde{S} are diagonal. Then a number of authors have proposed solving the linear system $Ax = b$ by solving the normal equations for one of the preconditioned systems

$$(11a) \quad \hat{A}_1 \hat{x} = [\tilde{S} (\tilde{D}+L)^{-1} A (\tilde{D}+U)^{-1}] [(\tilde{D}+U) x] = [\tilde{S} (\tilde{D}+L)^{-1} b] = \hat{b}$$

(see [12]) and

$$(11b) \quad \hat{A}_2 x = [(\tilde{D}+U)^{-1} \tilde{S} (\tilde{D}+L)^{-1} A] x = [(\tilde{D}+U)^{-1} \tilde{S} (\tilde{D}+L)^{-1} b] = \hat{b}$$

(see [14, 3]). $\hat{A}_2 \hat{p}$ can be computed as

$$(12) \quad \hat{A}_2 \hat{p} = (\tilde{D}+U)^{-1} \tilde{S} [\hat{p} + (\tilde{D}+L)^{-1} (D+U-\tilde{D}) \hat{p}]$$

in $4N + NZ(L) + 2NZ(U)$ multiply-adds, whereas $\hat{A}_1 \hat{p}$ can be computed as

$$(13a) \quad \hat{t} = (\tilde{D} + U)^{-1} \hat{p}$$

$$(13b) \quad \hat{A}_1 \hat{p} = \tilde{S} [\hat{t} + (\tilde{D} + L)^{-1} (\hat{p} - (2\tilde{D} - D)\hat{t})]$$

in $4N + NZ(L) + NZ(U)$ multiply-adds. Thus the first approach would be more efficient per iteration, although more iterations might be required to achieve comparable accuracy [14].⁶

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⁶ The same would be true if a Generalized Conjugate Residual method such as Orthomin [15, 8] were used to solve (11a) or (11b).

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